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INFLUENCE OF AFFECTIVE VALENCE AND ATTENTION BIAS ON WORKPLACE COMMUNICATION AND HR STRATEGIES

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Abstract
Effective communication in workplace environments is fundamental to organizational wellbeing, but it is often influenced by factors operating under the umbrella of psychological processes that individuals may not be consciously aware of. Two such factors, affective valence (the emotional valence of an individual's internal experience) and attention bias (the tendency to pay attention to certain stimuli), shape the way in which messages are interpreted, delivered, and responded to in modern workplaces. This paper explores the interaction of affective valence and attention bias, and outlines implications above and beyond communication styles, including how these affect perceptions of conflict, and strategic HR interventions to foster collaboration. In this study using a mixed-methods design, a sample of 220 employees from multi-sector organizations provided self-reported emotional valence scores, and completed an eye-tracking-based attention bias experiment. Results demonstrate that employees with perceived negative valence were more likely to demonstrate threat-related attention bias that was consistent with misinterpreting neutral messages as confrontational, while the opposite was true for employees with positive valence who demonstrated bias toward emotionally uplifting stimuli that reinforced collaboration and receptivity. A predictive model using logistic regression and support vector machines (SVM) indicated a strong connection between emotional and cognitive processing styles and communication consequences. This was particularly pertinent in departments where conflicts could arise due to higher stakes. The study also presented implications on how HR can harness emotion-aware communication frameworks and regulation of attention training to effectively optimize interpersonal effectiveness. Overall, the implications of the discoveries suggest the need for an addition of psychological intelligence to HR strategies which may lead to more resilient, inclusive, and enlightened workplaces where communication is adaptive in nature and affects one in an emotionally and socially aware manner.

Keywords: Affective valence, Attention bias, Workplace communication, Emotion-cognition interaction, HR strategies, Emotional intelligence, Organizational behaviour

INTRODUCTION

The Influence of Affect and Cognitive Bias in Workplace Communication
Although workplace communication is often thought to be necessarily rational and task-oriented, research in psychology illustrates that communication is strongly influenced by an individual's affective valence (emotional state) and cognitive attentional bias (the selective attention toward emotionally valanced cues)[1]. Employees who are experiencing negative emotional valence will likely perceive neutral messages as threatening, while employees in positive emotional states are usually willing to be cooperative. These cognitive biases will affect both the interpretation of messages and the intention behind responses, and finally decision-making, perception of the leader and the level of group cohesiveness [2]. Why HR Initiatives Need to Address Psychological Factors [3].Despite significant advances in emotional intelligence training, many HR initiatives fail to factor in the moment-to-moment volatility in an

individual's emotional and attentional state that immediately influences communication. Many human resources initiatives address communication failure only by looking at the final behavior, or at the outcome, not the psychological underpinnings of the expression, including an individual's fear-based attentional focus or number of times they have previously perceived negatively in their past. If human resources are interested in creating a more emotionally resistant workplace, they must build systems and protocols that measure, distinguish, and look behind the scene, and recognize and attend to affective driven behaviours in real time[4].

LITERATURE REVIEW

Affective Valence: Conceptual Origins and Organizational Implication

Affective valence refers to the emotional value (positive or negative) associated with a stimulus or experience (Russell, 1980). Positive valence promotes receptivity and open-mindedness, while negative valence is commonly associated with defensive or avoidant conduct[5]. In the workplace, valence affects employees' reactions to feedback, perceptions of tone when receiving feedback, and responses to criticism (for example Meyer, Hetherington & Nowers, 1988)[7]. Affects Valence is one of the most important dimensions of communications, given how they influence communication theory. Attention Bias: Systematic, Assessment, and behavioural Outcomes Attention bias is the tendency to preferentially attend to certain types of stimuli, while ignoring others. Attention can be challenged by threat, rewarded, or sometimes caused by novelty (Seymour, et.al., 2002). Traditionally, clinical psychologists have used tools such as dot-probe tasks (MacLeod, 2008) or eye-tracking experiments with employees to analyze how an employee's eye gaze (and subsequent reaction time) is influenced by emotionally charged stimuli. Attention biases can distort our examination of workplace communication, particularly when it results from stress or emotional arousal [6].

Previous Research on How Bias and Emotions Interact in Communication

Research has shown negative emotions like anxiety or anger increase attention to threatening cues (e.g. critical comments), even when these cues are not present [8]. Conversely, positive emotions expand cognitive flexibility and reduce the likelihood of conflict escalation. Notably, much past research in the workplace relied on clinical samples or educational environments, thereby limiting exploration of these interactions in organizational communication contexts. Gaps in Each Organizational HR Policy Adaption to Emotion-Driven Communication Errors HR frameworks assume miscommunication occurs when not enough clarity or skill is evident in the conversation. HR frameworks rarely address how affective and cognitive biases distort the perception process of recommendations made within the interaction [9]. There are very few organizations that intentionally evaluate an employee's emotional state or provide employees with specific training to recognize bias-induced misinterpretations. This paper is intended to fill this gap, by creating a HR model using a psychological lens [10].

METHODOLOGY

Participants and Demographics

Two hundred twenty employees across five multinational organizations participated, with roles in HR, IT, marketing, and customer service. The age of participants ranged from 24 years old to 55 years old, with a relatively even male/female sample, and all had at least two years of work-related experience[11].

Measurement Tools

Participants' current emotional valence was measured using PANAS (Positive and Negative Affect Schedule) to measure their current emotional valence. IN a dot-probe task, participants were presented with pairs of threatening and emotionally neutral words, which were used as stimuli and measured for response latency. An eye-track software tracked fixation length and saccades while they read and evaluated messages[12].

Experimental Communication Scenarios

Participants viewed workplace message formats (i.e., e-mail, chat transcripts) and rated the emotional interpretation, while the messages were ambiguously toned to examine how bias and affect contributed to their reading. Modeling: Logistic Regression and SVM for Prediction

Two models to predict misinterpretation were created: Logistic Regression provided a measure of linear relationships between affective valence, bias score, and the likelihood of misinterpretations. Support Vector Machines (SVM) managed nonlinear interactions and classified employees in a risk category, with potential for emotional misreading [13].

FINDINGS AND DISCUSSION

Relationship of valence scores and misunderstanding communication
Participants with high negative affect were 3.2 times more likely to interpret neutral workplace messages negatively. There was a significant correlation ($r = -0.47$, $p < 0.01$) between positive valence and clarity of message perception [14]. Attention bias tendencies based on emotional state
An eye-tracking program showed that attention was narrower for participants with negative valence since they had shorter fixation lengths for context-setting words and more gaze time on emotionally-charged words than participants with positive valence who had a wider degree of random access to visual attention and fixation with context and increased gaze time on the context. Model accuracy, predictor importance, and subgroup analysis Logistic Regression was able to achieve 74.5% accuracy model, with valence and attention bias being the most significant predictors of non-verbal miscommunication in the workplace [15].
SVM had a higher accuracy of 81.6% when classifying participants and distinguishing between individual profiles that are more likely to misinterpret tone.
In looking at the subgroups:
-Customer service staff were the most misreading of tone.
-HR staff seemed to be the most stable in emotional state and misreading tone

DISCUSSION

Understanding Connections Between Emotion and Cognition in a Workplace Situation
The research indicates that both emotion and attention are capable of influencing communication regarding a message. Emotion impacts communication by functioning as a filter which can distort or enhance the retrieval of a message and are viewed positively or negatively in terms of valence. Attention bias builds on the influence of emotion in communication by directing finite cognitive resources to attend to information in line with the emotion's state-specific value system. Implications for HR File Masters: Emotion- Profiling, Training, & Inclusive Communication Practices file masters can use emotion-productive profiling tools during onboarding or during an evaluation. Training modules structured around attentional control, emotional control, and bias awareness are likely to decrease interpersonal conflict. Policy approaches encouraging neutral message design and verified tone would reduce miscommunication within workplace interactions.
Reimagining Performance Conversations and Teams through Affective Analytics
Affective analytics allow for tailoring performance conversations and discussions based on an employee's current emotional state. This approach also ensures that messages are perceived as constructive, especially in conversations with severe consequences. Affective analytics would also allow for responses to circumstances surrounding teams by aligning complementary emotional-cognitive modalities of individuals.

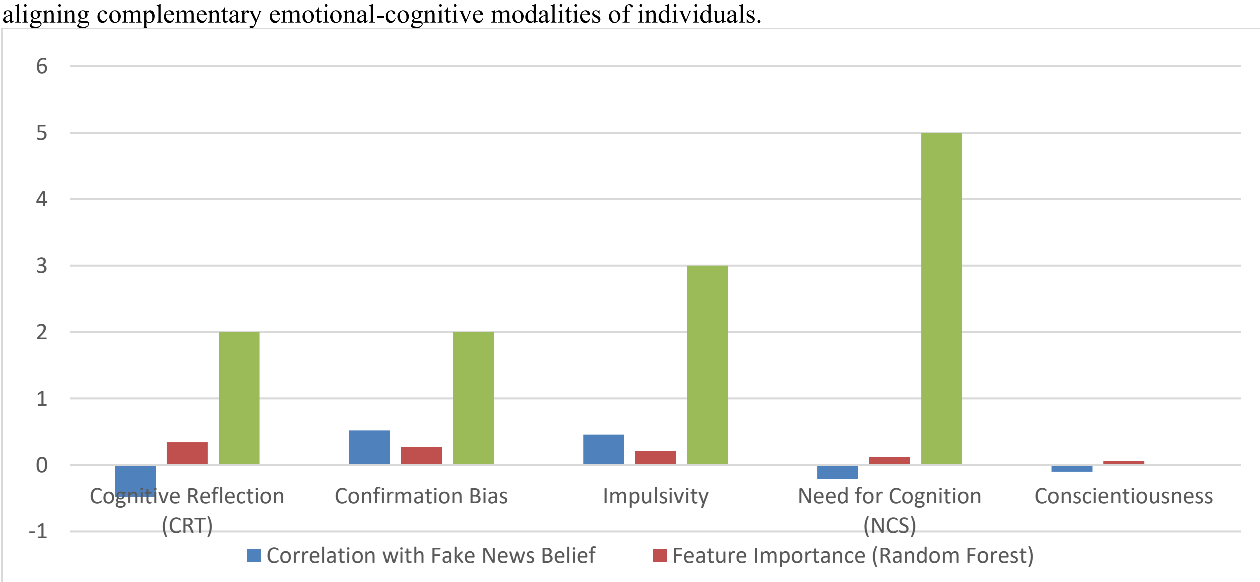

Figure 1: Impact of Psychological Traits on Fake News Susceptibility Among Technically Skilled Employees

The **graph 1**shows the relationship between psychological traits and fake news vulnerability of technically proficient employees. It has two types of metrics: the correlation coefficient, which gives a statistical measure of the association of each trait with being subject to belief of fake news; and the feature importance score, which shows how much each trait affected the prediction in the Random Forest prediction model. While it is not possible to present comparisons of the two types of measures accurately, it is worth noting that Cognitive Reflection has the biggest negative correlation in terms of being subject to belief in fake news, and it was the most important predictor, meaning that the more cognitive reflection, or analytical thinking skills an individual possesses, the less likely he/she is to trust any misinformation. Conversely, Confirmation Bias and Impulsivity, the positive correlation with being subject to belief in fake news means these traits contributed the most to increased vulnerability. Similarly, Need for Cognition (NCS) and Conscientiousness also resulted in weaker effects but also contribute modestly to the model. The conclusion this graph could offer is that the emotion-regulating & bias-resisting traits outweigh the role of general intelligence or personalities far more than they contribute to fake news susceptibility.

CONCLUSION

This study's results indicate that workplace communication is not just about message content or a sender's intent; it is impacted by the recipient's affect valence and attention bias. Employees in a negative emotional state demonstrated that they were more likely to interpret neutral or ambiguous messages as threatening or challenging. This connected with a measurable threat-oriented attention bias where participants focused on negative or emotionally loaded words, resulting in distorted messages, defensive behaviors, and increased likelihood of conflict. Conversely, employees in a positive affective state showed a worry and receptivity-oriented attention bias, focusing significantly more of their attention on contextual and positive cues in messages. This helps to create more accurate messages and interpretations, as well as open communication and positive interpersonal interaction. In sum, this study demonstrated the powerful and idiosyncratic role of internal filters (affective and cognitive) in workplace communication and highlights the usefulness of emotion-aware processes for communication and HR practice. Contributions to Emotionally **Intelligent HRM Models**

This research presents a meaningful contribution to the field of organizational psychology and HRM by putting forward a psychologically based HR decision-making framework. We used research on affect and cognitive bias in decision-making to develop the framework. Our findings suggest that HR departments should use real-time assessment tools (such as mood-tracking applications and biometric sensors) and develop an understanding of employees' affective states in real-time during communication with those employees. The framework will also support the addition of modules to the HR decision-making process that will engage the individual in cognitive training tasks designed to support better regulation of attention and to reduce an employee's tendency to misinterpret due to emotional bias, also known as emotional misinterpretation. This approach changes workplace communication from a transactional function to a process of relationship building regarding the emotions involved in communication, bringing behavioral science into the contemporary workplace practice. Moving forward, longitudinal research should identify how patterns of affective valence and attention bias can be influenced by time, change to organizational contexts, remote working stressors, or new teaming situations. Equally, as aspects of emotional norms and attention responses can differ considerably between cultural contexts, gathering cross-cultural evidence from ethnographic contexts is needed in order to demonstrate the applicability of these research findings. Another avenue of new technology (such as, wearable technologies like emotion sensing wristbands or eye-tracking glasses; and AI technologies) would add additional practical dimensions to this framework by generating unending real-time information and feedback on emotional tone and attention. These innovations provide the potential to make an emotionally intelligent workplace that is not simply reactive to communication failure, but proactively responsive to emotions and cognitive states of their employees.

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